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FINDING CURVES IN SAR CCD IMAGES

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ABSTRACT

This paper introduces a pattern recognition and computer vision approach to mitigating false alarms in synthetic aperture radar (SAR) coherence change detection (CCD) images. In this paper, we perform an automatic detection of roads in SAR CCD images. The approach is based on a curve tracing algorithm originally proposed by Steger with modifications to better suit the goal of curve detection in SAR CCD images [1]. In our technique, the traditional Steger's method is used to detect curve points, and cubic splines are used to approximate the original curve. To detect roads more accurately, preprocessing and outlier removal techniques are performed along with the curve detection.

Index Terms— SAR, CCD, change detection, curve detection, regression splines

1. INTRODUCTION

Synthetic aperture radar (SAR) coherence change detection (CCD) is a sensitive change detector that is capable of detecting scene changes that are on the order of a radar wavelength, which is much smaller than the spatial resolution of SAR images. SAR CCD uses a traditional technique called interferometry that utilizes magnitude and phase information in two (or more) SAR images collected from nearly identical geometries to detect small (sub-wavelength) changes in elevation between collections [2]. These small elevation changes result in a low coherence (estimated using the two datasets) in the specific areas of change. This sensitive detector is capable of detecting small ground disturbances such as tire tracks. Change is detected in areas of low coherence between the two SAR images, but unfortunately, low coherence can result from phenomenon other than change (at least change of interest) such as radar shadows and vegetation that "changes" as a result of weather conditions. While some attention has been devoted to improving coherence calculations and establishing frameworks by which certain false alarms may be discriminated from actual change, little or no research has been devoted to using known pattern recognition and computer vision techniques to identify change of interest such as long, thin tire tracks amid the numerous false alarms. The purpose of this paper is to address this problem by introducing a new algorithm to detect curved lines (such as roads) in SAR CCD images using a computer vision and pattern recognition approach. The rest of the paper is organized as follows. Section 2 provides a background on SAR CCD and a survey of work done in the field, and Section 3 describes our new curve detection algorithm for SAR CCD images. Section 4 contains the results of our algorithm applied to sample images, and Section 5 concludes the paper.

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2. BACKGROUND

The sensitive detection capabilities of SAR CCD (as described above) have utility in applications such as aircraft search and rescue where the size of the aircraft is smaller than the radar resolution [3], and detection of vehicle movements due to earth disturbance caused by tire tracks [4]. The ability of SAR CCD to detect subtle scene changes makes the detection of foot prints and small objects (smaller than radar resolution) possible.

In order to detect such small changes, false alarm rates should be driven down through improved CCD processing and pattern recognition techniques. [5] characterized processing requirements for high coherence over areas of non-change. Once two SAR images are properly aligned, calculation of coherence is straightforward [5]. Several modifications to the standard coherence metric [2] have been proposed. One suggestion includes using the mean backscatter power ratio (standard in non-coherent change detection) in addition to coherence to reduce false alarms caused by low radar return [6]. Similarly, [7] proposed a new set of basis vectors for coherence correlation in an attempt to create features that can be used to discriminate between low coherence areas of change and non-change. One such feature identifies areas of low radar return (radar shadows), and the combination of low radar return and low coherence was identified as a region likely to cause a false alarm [7].

Our approach differs from the above in that we want to detect features of interest such as long thin lines indicative of tire tracks and roads. The following section describes the computer vision and pattern recognition techniques used to separate the linear areas of low coherence from other areas of low coherence.

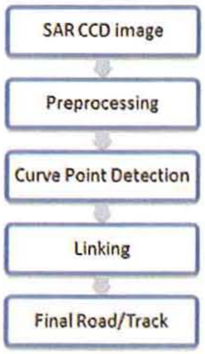

Fig. 1. Overall flow of our road detection algorithm.

3. CURVE DETECTION ALGORITHM

Our proposed curve detection algorithm is composed of several steps, as indicated in Fig. 1. To detect curves, we first preprocess an image by smoothing and applying a threshold to exclude false alarms before the extraction of curvilinear features. The curve points are extracted from the preprocessed SAR CCD images in accordance with Steger's method [1]. The next step is linking the curve points to form contiguous curves using a novel cubic spline fitting method, which produces the final road/track. These steps are described in more detail below.

3.1. Preprocessing

Examples of SAR CCD images used for the proposed method are given in Fig. 2. These images are 4096×4096. To extract curve points more accurately, two steps of preprocessing are performed: smoothing and thresholding. In the smoothing process, the input image is convolved with a filter bank that contains four first order derivative of Gaussian filters in different orientations, 0^o, 45^o, 90^o, and 135^o. Smoothing the image with the filter bank reduces noise and unwanted details and textures. From the four filtered images, the norm of gradient is computed and then a 30 percent threshold level between minimum and maximum intensity of the image is used to improve the signal to noise ratio.

3.2. Detection of Curve Points

In this paper, we are using an adapted version of Steger's method for finding curvilinear structures in 2-dimensional

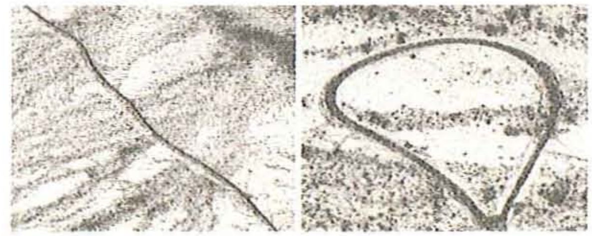

Fig. 2. Example SAR CCD images containing roads and false alarms caused by vegetation and radar shadows.

images [1]. Steger states that curvilinear structures in a 2-dimensional image can be modeled as curves, $s(t)$, that exhibit a characteristic 1D line profile (shown in Fig. 3). Let the direction perpendicular to $s'(t)$ be $n(t)$. The 1D line profile of a curve point is characterized by a vanishing first derivative and the largest absolute value in the second derivative. Thus, at a curve point, the first derivative in the direction $n(t)$ should vanish and the second directional derivative should be of large absolute value. A pixel in an image is classified as a curve point if the first derivative along $n(t)$ vanishes within a unit square centered around the pixel. Computation of the direction, $n(t)$, for a pixel can be tackled by finding the eigenvector that corresponds to the maximum absolute eigenvalue of the Hessian matrix of the pixel. The Hessian matrix consists of the partial derivatives, $\mathbf{r}_{xx}$, $\mathbf{r}_{xy}$, $\mathbf{r}_{yx}$ and $\mathbf{r}_{yy}$, of the image after convolving with a Gaussian smoothing kernel. This full detection process is performed for each pixel to find all the pixels that lie on a curve.

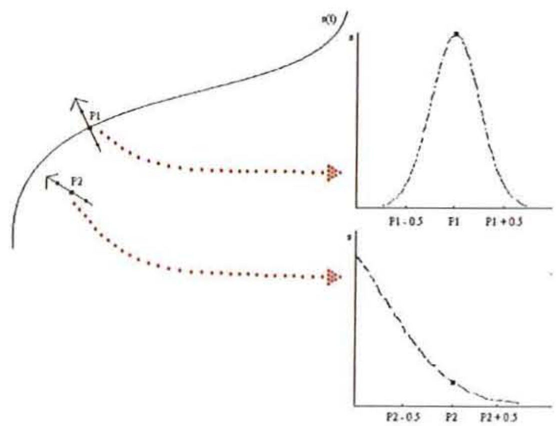

Fig. 3. Classification of curve points.

In Fig. 3, two points, P1 and P2, and their directional vectors are shown as an example. The directional vector at a pixel point represents the direction of greatest curvature. It is computed by finding the eigenvector that corresponds to the greatest eigenvalue of the Hessian matrix at each pixel. In Fig. 3, the point P1 is declared a line point because the first

directional derivative vanishes within the current pixel. However, the point P2 is not declared a line point because the first directional derivative does not vanish within the pixel boundary of P2.

3.3. Linking of Curve Points

After individual curve points have been extracted using Steger's method, they need to be linked to form curves. Steger proposes a local linking algorithm that uses the orientation information of three neighboring pixels obtained in the classification step and joins curve points appropriately to form curves. However, this method is not sufficient with SAR CCD data due to its noisy nature (especially after filtering and thresholding). The ideal curve tracing algorithm in SAR CCD data should incorporate both local and global structure. We propose a global linking algorithm and outlier removal method that uses cubic splines to approximate the SAR CCD curve points. Cubic splines are piecewise polynomials with continuous first and second derivatives at the knots (the points where the pieces meet), which allows them to flexibly model complex curves. Though splines are often used for interpolation, we are using them here in a smoothing or regression sense. The objective is to find knots that minimize the sum of squared distances between the detected curve points and the spline defined by the knots.

Once curve point detection is done on individual block images, we can stitch the partitioned images back together. The result is shown in the left of Fig. 4, where we observe that curve detection false alarms are still present within the overall image.

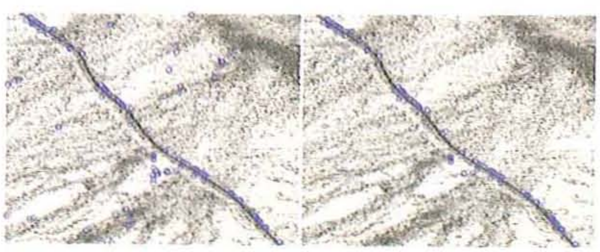

Fig. 4. Outlier removal using spline interpolation.

In SAR CCD images, due to the small number of significant data points, outliers can have a large influence and may cause serious bias in the estimation process. To reduce the influence of outliers on curve detection, we perform linking in three steps: (1) fitting a provisional cubic spline to all data points in the stitched image, (2) removing data points that fall far from the spline curve, and (3) fitting a final cubic spline to the remaining points.

Finding the best-fitting spline for a given set of data points can be formulated as a nonlinear optimization problem where the decision variables are the knot locations. Because the objective function does not have an obvious closed form, we approximate its partial derivatives with centered differences, and then minimize the objective function with gradient descent. Here we use the iRprop algorithm [8], a first-order method that adapts individual step sizes for each parameter being optimized using only the sign of the partial derivative.

To seed iRprop with a good initial solution, we apply k-means clustering [9] to the detected curve points and use the cluster centroids as the initial knot locations. However, the clusters that k-means outputs are not necessarily ordered in a spatially meaningful way. We rectify this by reordering the knots using 2-opt, a traveling salesman problem heuristic [10]. The iRprop method then refines the knot locations starting from these good initial estimates. Fig. 5 shows a spline curve before and after fine-tuning.

In the first step of the linking process, we fit a spline with five knots (five clusters in the k-means initialization) in order to obtain the general trend of the curve. In step 2, the ten percent of the curve points that fall farthest from the spline are defined as outliers and removed from the data. Fig. 4 shows detected curve points before and after outlier removal. Finally, we fit a spline with 10 knots (10 clusters in the k-means initialization) to find a more accurate representation of the curvilinear feature. This final spline is used to represent the road from the original SAR CCD image.

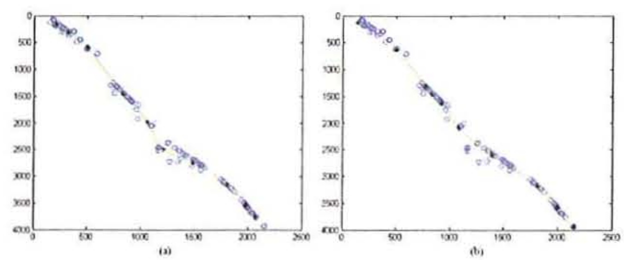

Fig. 5. Spline interpolation. ((a) Initial spline interpolation. (b) Final spline interpolation.)

4. EXPERIMENTAL RESULTS

We applied our algorithm to SAR CCD images collected in Yuma, AZ in April 2008 using Boeing's Ku-band Compact Radar and a King Air 300 aircraft. This radar has .25 meter range and cross-range resolutions. The CCD images, shown in Fig. 2, were constructed using SAR images that were collected at least one day apart.

Fig. 6 shows examples of the results obtained with our approach. Based on visual inspection of the resulting images, we can observe high probability of detection and low probability of false alarm in Fig. 6 (a). Detected curve points are denoted as blue dots and refined knots are denoted as magenta asterisks. There are not enough curve point detections to form a contiguous line, but there are enough points to learn the general trend of the line through linking. One main advantage of

approximating the road using cubic splines is that the method is robust to sparse data that contains a small amount of significant information. As shown in Fig. 6 (a), the locations of the knots are not limited to specific coordinates of detected curve points, but are estimated by gradient descent optimization. Since splines are defined piecewise, they are able to model complex curves in real SAR CCD images such as roads and tracks. However, the first knot is not necessarily connected to the last knot and this explains the discontinuity in the circular road in Fig. 6 (b). From Fig. 6 (b), it appears that the straight roads are detected almost perfectly but non-linear roads suffer from minor digressions and discontinuities.

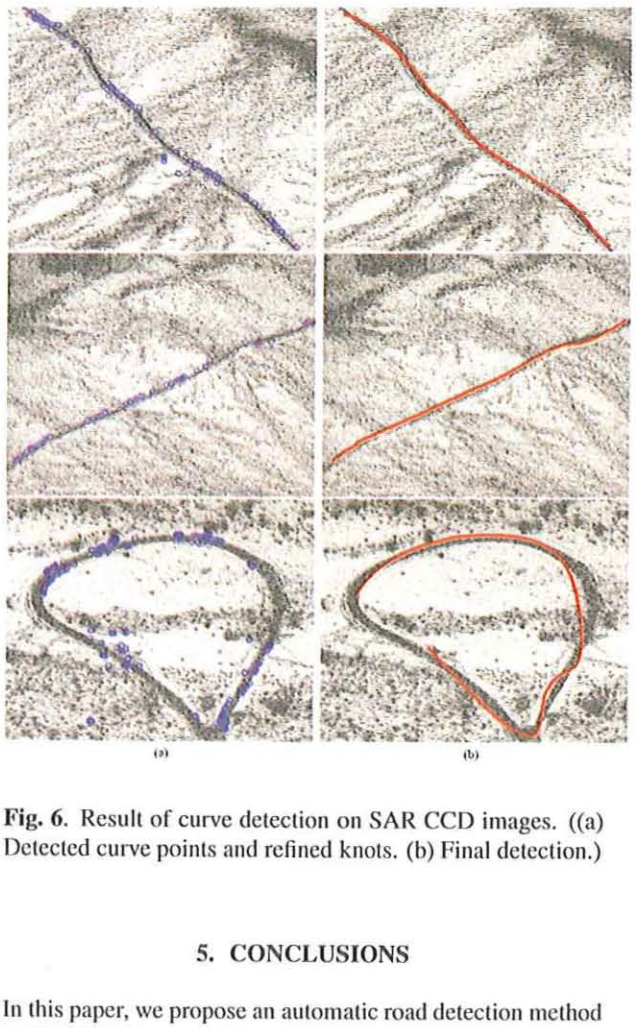

Fig. 6. Result of curve detection on SAR CCD images. ((a) Detected curve points and refined knots. (b) Final detection.)

5. CONCLUSIONS

In this paper, we propose an automatic road detection method in SAR CCD images. Our method treats roads in SAR CCD images as curvilinear structures and detects the curve points on those roads. We finally use a gradient descent optimization method to minimize error in cubic spline curve fitting to extract the road using global information in detected curve points. Road detection on SAR CCD images has never been explored in the field of image processing and we are the first ones to apply such an algorithm on SAR CCD data. Experimental results show that the proposed method can extract roads with reasonable accuracy even with SAR CCD noise and false alarms. Future work may include automatically choosing the number of knots, dealing with closed curves, and handling scenes containing multiple curves.

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